REAL-TIME IMAGE ENHANCED DATA-DRIVEN DIGITAL TWIN (REAL-TIME 3DT) FOR CSP FLUX DENSITY MEASUREMENTS

SOLARPACES 2024

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SolarPACES Solar Power & Chemical Energy Systems | Marie Skłodowska--Curie Actions | TOP CSP | DLR

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Introduction

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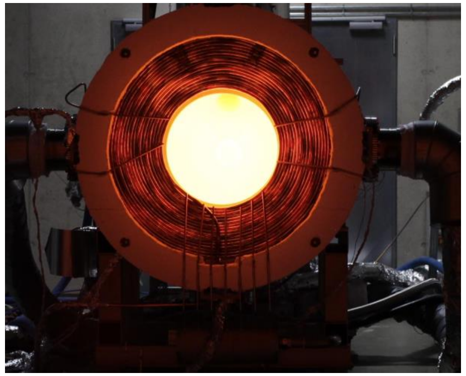
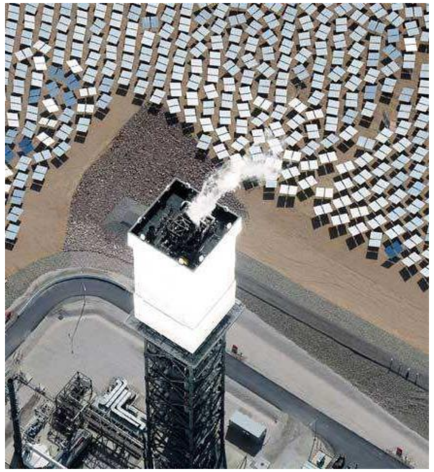
INTRODUCTION: TYPES OF RECEIVERS

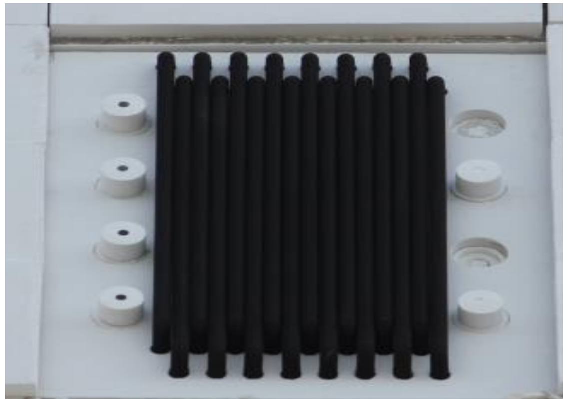
Solar power towers → Increasing variety of receivers' geometries

Receivers

- Cavity
- Open volumetric
  - Flat
  - Curved
  - Cylindrical
- Tube



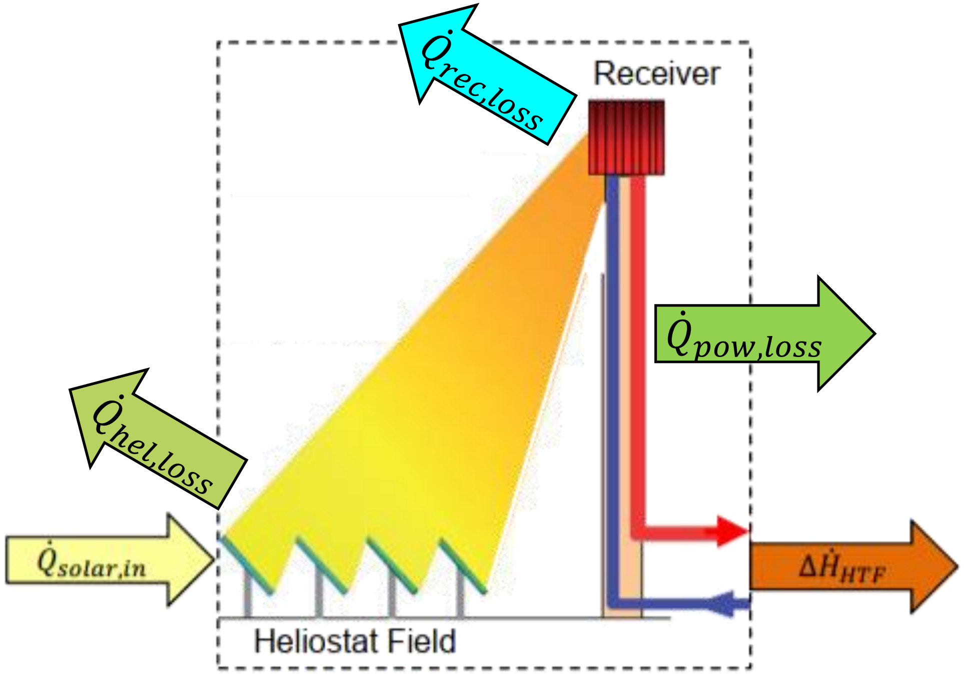




Synhelion → Industrial in this project

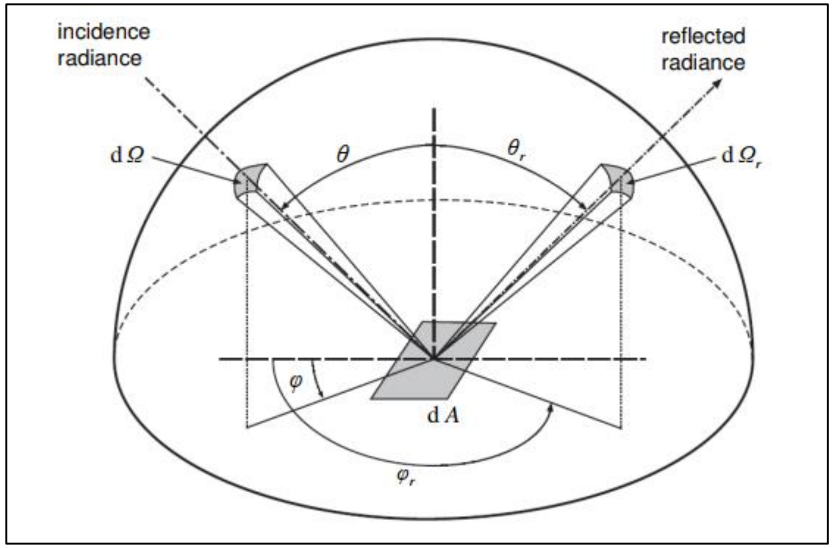
INTRODUCTION: FDM RELEVANCE

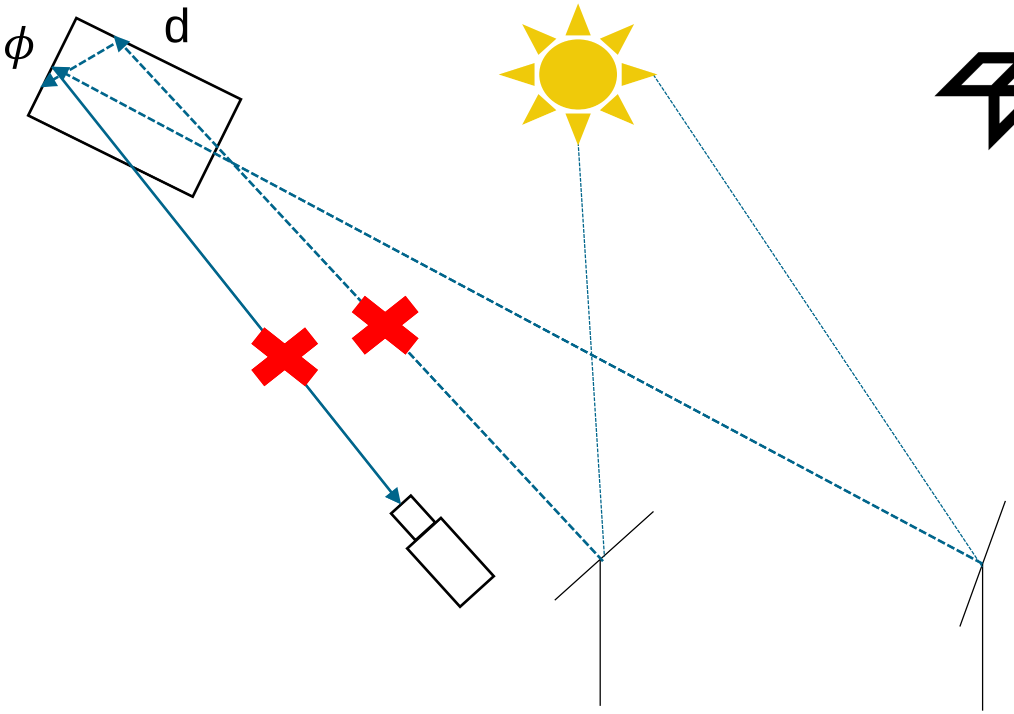
- Flux Density Measurement (FDM) in the central receiver
  - Enhancement of average performance
  - Accurate tracking of heat losses → Possible decoupling between heliostat measurements and receiver measurements



Challenges:
- Universality
- Continuous and non-disruptive
- Harsh conditions
- Computing power
- Processing time

INTRODUCTION: MOTIVATION





$$\rho(\theta,\varphi,\theta_r,\varphi_r) = \frac{L_r(\theta,\varphi,\theta_r,\varphi_r)}{L(\theta,\varphi)\cos\theta\, d\Omega} \longrightarrow \rho(\theta,\varphi,\theta_r,\varphi_r,d,\phi) = \frac{L_r(\theta,\varphi,\theta_r,\varphi_r,d,\phi)}{L(\theta,\varphi)\cos\theta d\Omega}$$

Now the BRDF is also a function of the geometry of the ca
diameter) → Disc
charact

- **Inherent perspective problems**: most of the
ptured in camera
reabsorbed by

Hybrid use of cameras and computing methods:
Real-**T**ime **Im**age **E**nhanced **D**ata-**D**riven **D**igital-**T**win **(Real-TImE 3DT)**

Aims

SolarPACES Solar Power & Chemical Energy Systems

Marie Skłodowska--Curie Actions

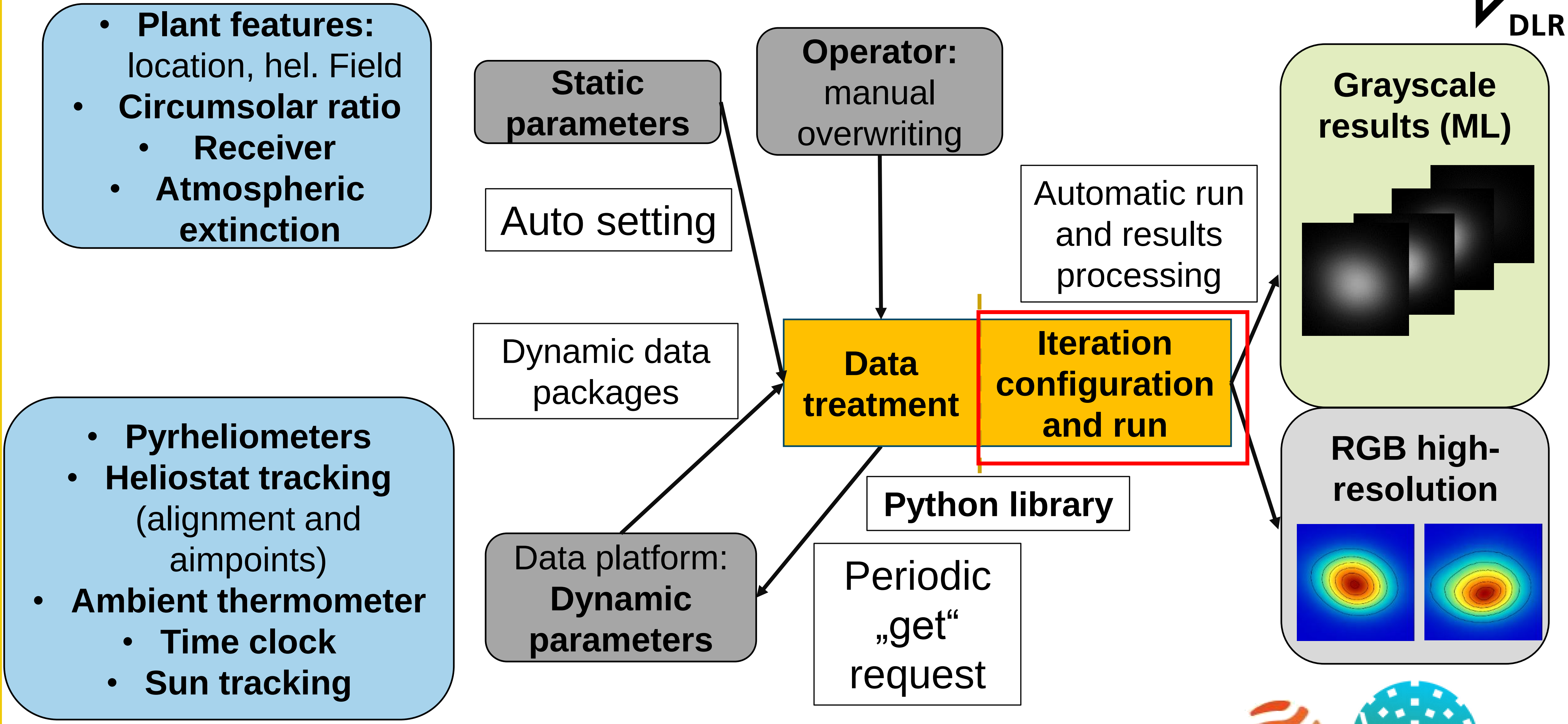
TOP CSP

AIMS

- (Near) real-time measurement
- Non-disruptive
- Easy user interface
- Connection between conventional measurements and possible future trends (data-driven models)
- Self-corrected with AI enhancement
- ***“Towards Smart CSP”***

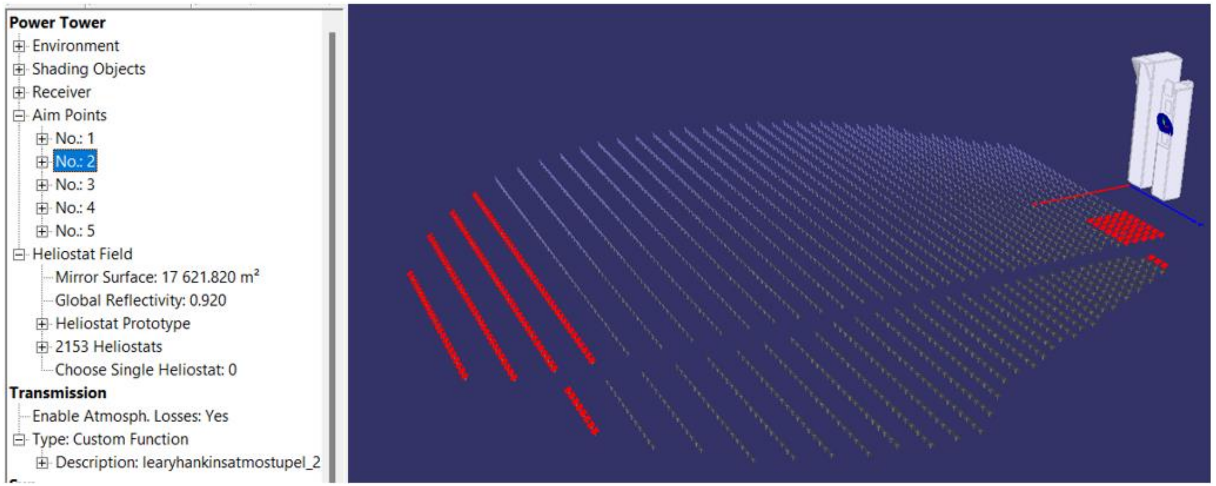
Methodology: digital twin

DIGITAL TWIN MODULE



DIGITAL TWIN MODULE: USER INTERFACES

STRAL: viewing tool

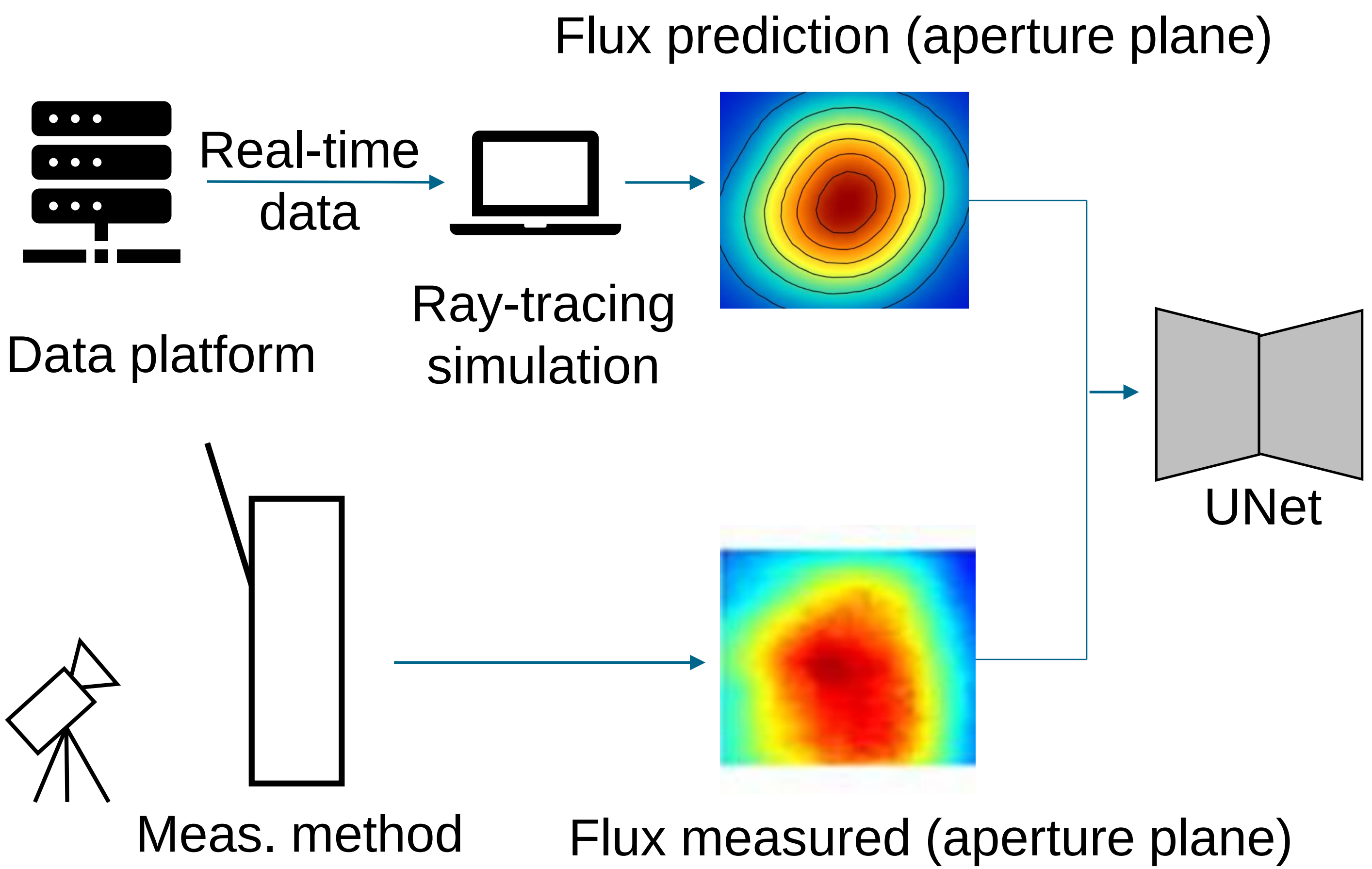


PYTHON: human-machine interface

```
#### INTRODUCE HERE THE HELIOSTATS TO BE ADJUSTED ######

#hel_list = [1,140,158,172,529,1032,1055,1111,1429,1932]

hel_list = [140,158,172,529,1032,1055,1111,1429,1932]
#hel_list = [1]

#### INTRODUCE HERE THE ADJUSTMENT: Defocus/aimpoint change/tracking error correction ######

defocus = False            # If the change is hel. defocus --> defocus = True (analog for the rest)

aimpoint_change = True    # Defocus and aimpoint change cannot be refered simultaneously to the same heliostat

tracking_error_correction = False

new_aimpoint = [0,0,0]  # Introduce here the aimpoint

new_tracking_error = [1.25,1.25,1.25,1.25]
```

Methodology: AI-enhancement

Real-TImE 3DT: TRAINING FLOW DIAGRAM



- **1st training phase: sim2sim**

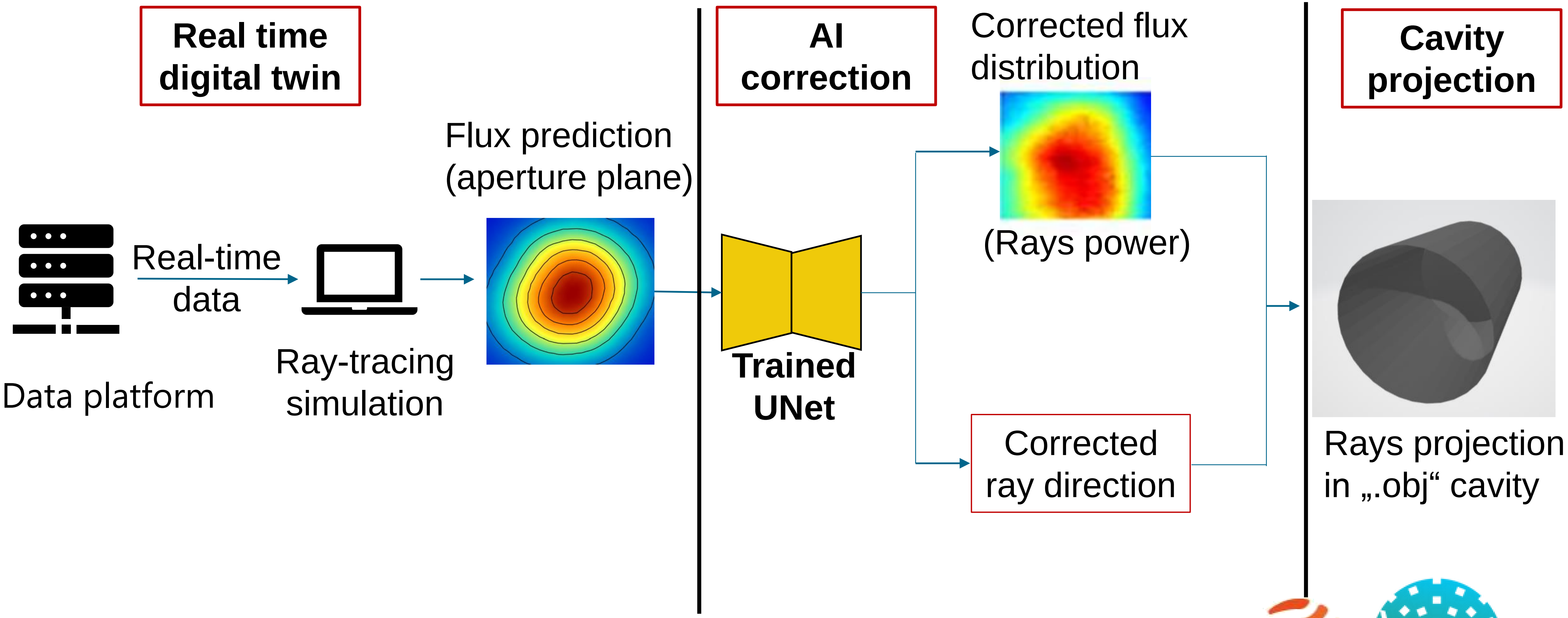
  Mapping simulation without tracking errors to simulations with tracking error

- **2nd training phase: sim2real**

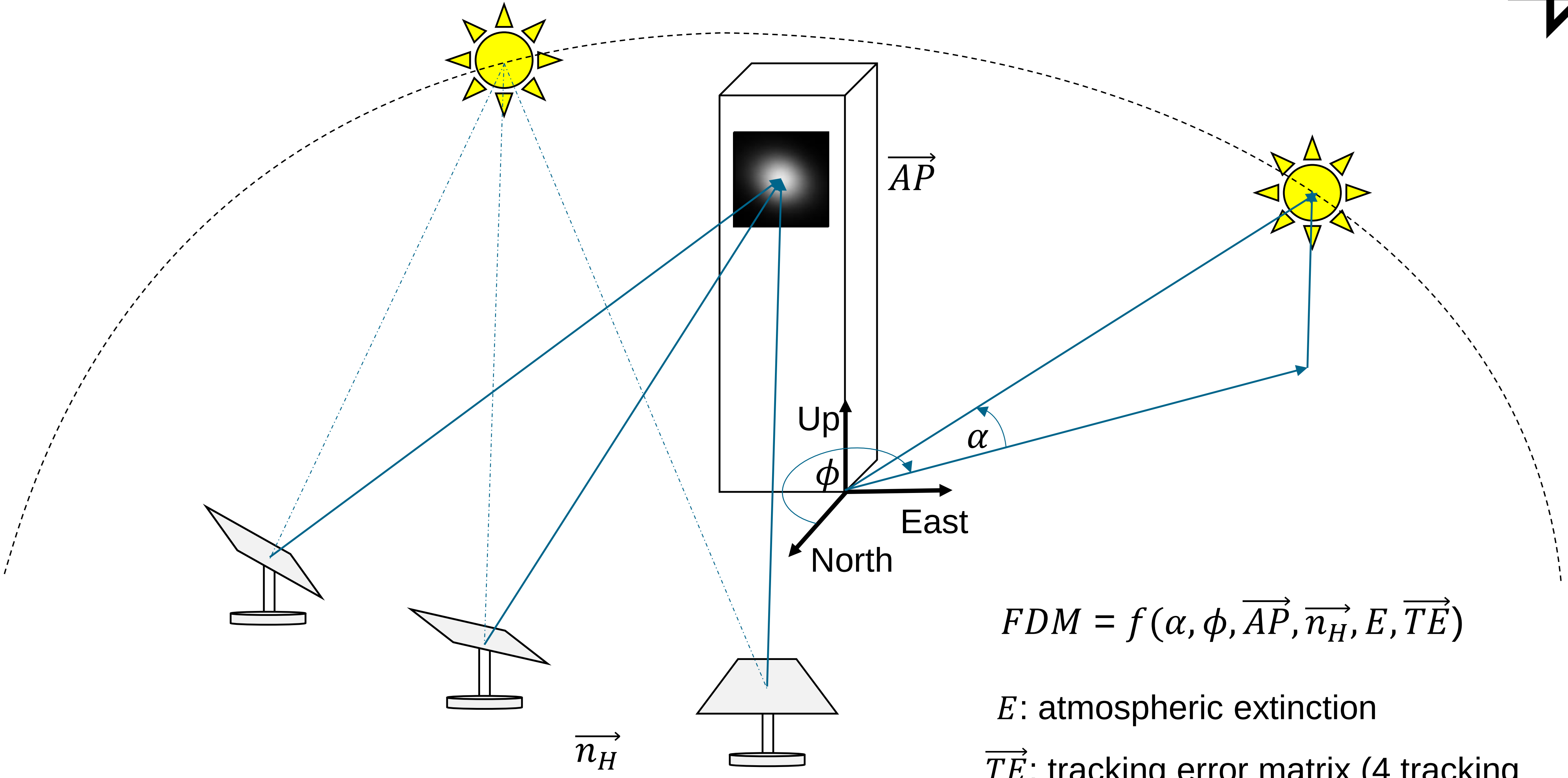
  Use pre-trained model to map from realistic simulation to real images obtained by measurement methods

Possible training out of working hours

Real-TImE 3DT: OPERATING FLOW DIAGRAM



METHODOLOGY: PARAMETRIC ANALYSIS



$$FDM = f(\alpha, \phi, \overrightarrow{AP}, \overrightarrow{n_H}, E, \overrightarrow{TE})$$

E: atmospheric extinction

$\overrightarrow{TE}$: tracking error matrix (4 tracking errors in 2153 heliostats)

METHODOLOGY: PARAMETRIC ANALYSIS

- **DNI, α and ϕ** → Parameters defining each of the atmospheric conditions (931) → Understanding of a deep set of different combinations of these parameters

- $\boldsymbol{E}$ → Leary Hankins model for the whole dataset (both label and input) → The neural network ignores this parameter

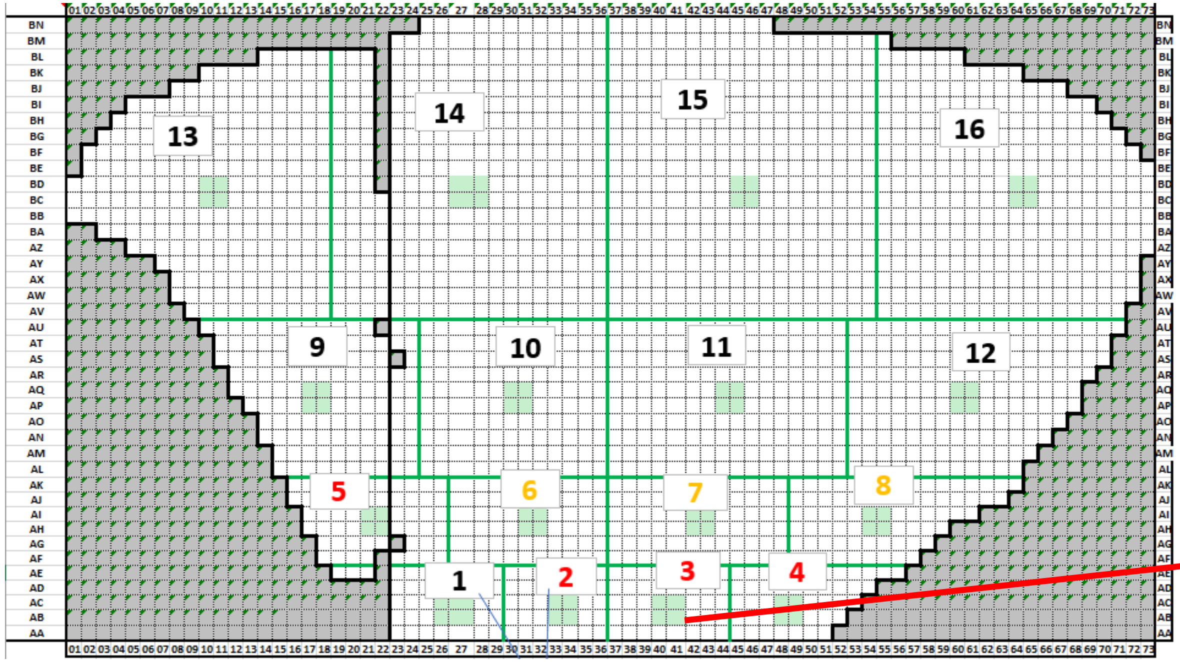
- $\overrightarrow{\boldsymbol{AP}}$ → Vector of aimpoints → Only one aimpoint centered in the cross of the cavity axis and the aperture plane (realistic approach for cavities)

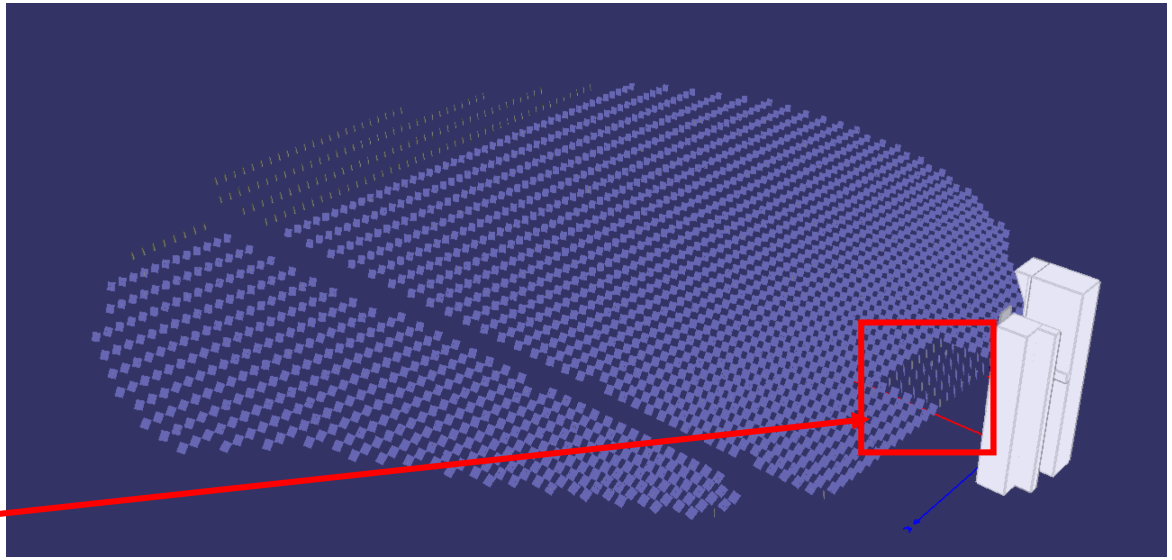
- $\overrightarrow{\boldsymbol{TE}}$ → Control variable → Used to validate the performance of the neural net → Present in label but not in input

Semicontrolled conditions

METHODOLOGY: PARAMETRIC ANALYSIS

- $\overrightarrow{n_H}$ → Array of active heliostats →16 areas considered; 931 cases for each defocused area → Implicit understanding for the model about the effect of each area of heliostats





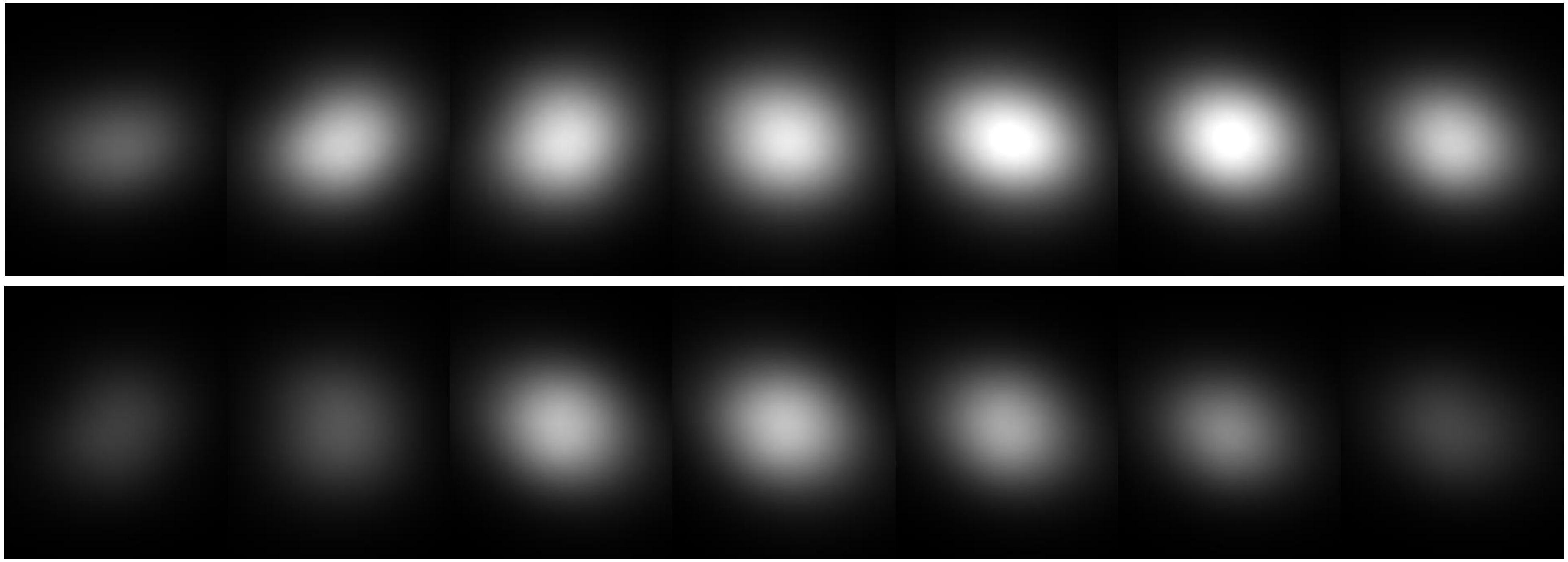
Areas are defined because it is impossible to know the functional dependency of each heliostat with the resulting DNI (2153 x 931 cases)

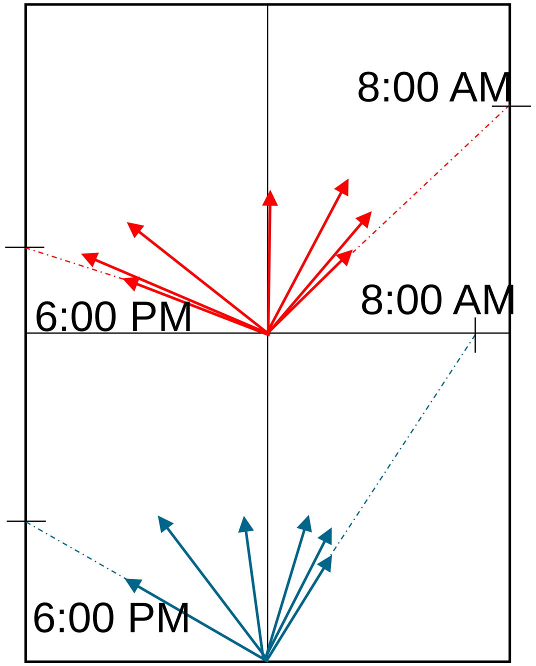
→

Synergy with Sun to Liquid II → IMDEA field is only composed of ~200 heliostats → Possibility to define smaller areas

METHODOLOGY: PARAMETRIC ANALYSIS

8:00 AM | 10:00 AM | 11:00 AM | 12:00 PM | 2:00 PM | 4:00 PM | 6:00 PM



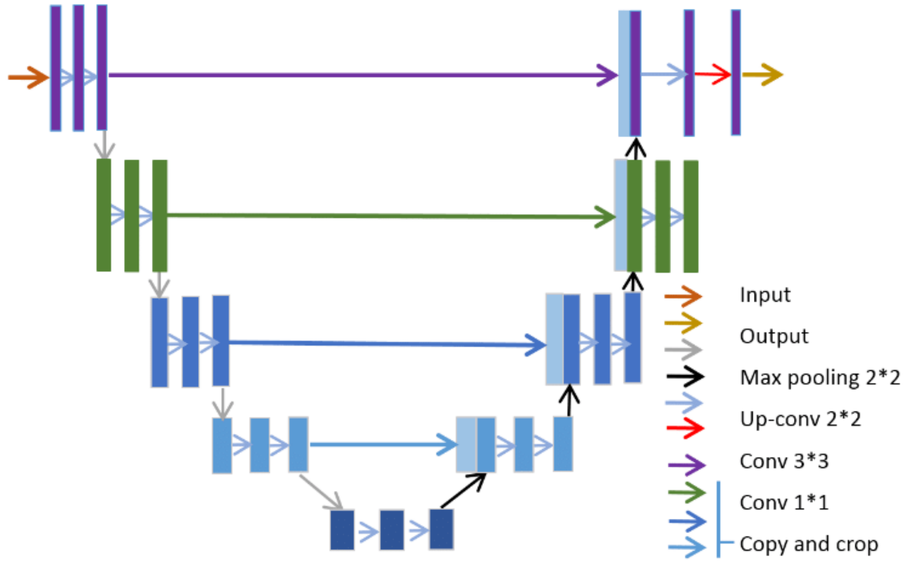


Repeated pattern during the different days in the shape and bright of the light beam

Direction and length of the longest radius of the beam

METHODOLOGY: U-NET CORRECTION

- **U-Net architecture developed**

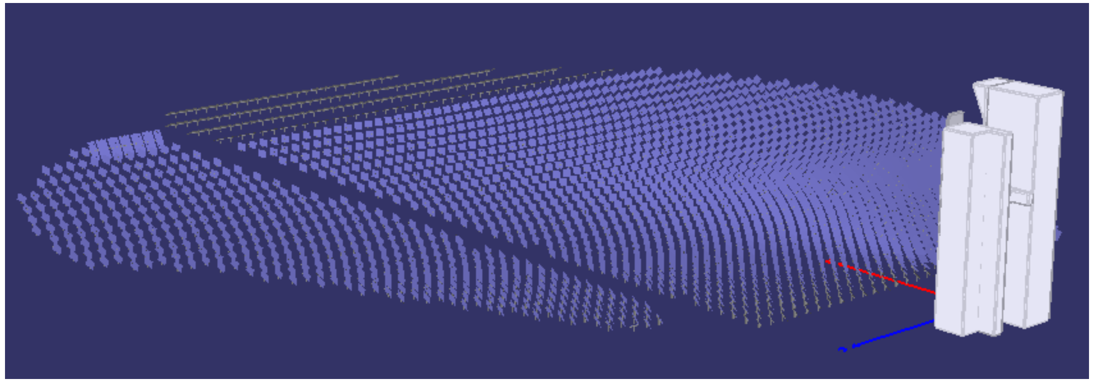


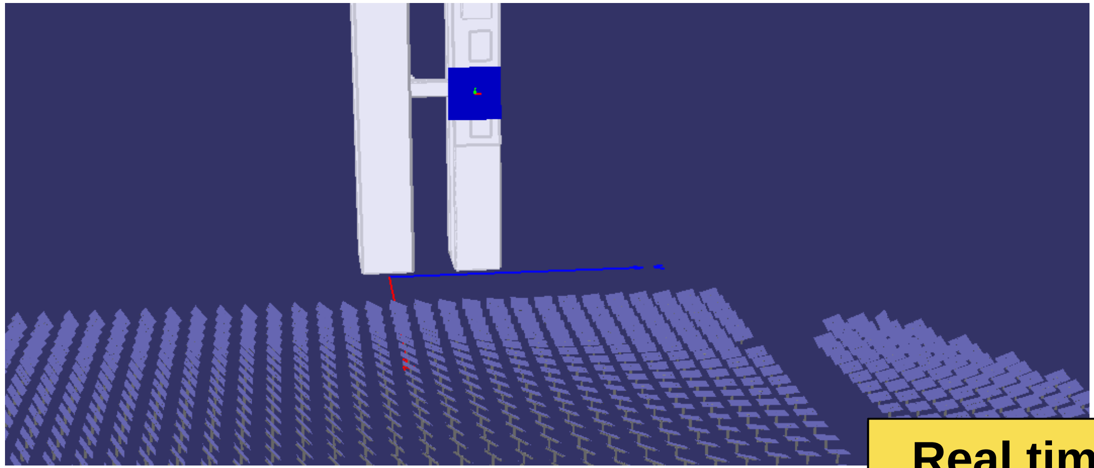
- **Dataset normalized [0,1]**
- **Images cropped and downsampled (256x256px)**
- **80% used for training**

Results: digital twin

RESULTS: PROOF OF CONCEPT

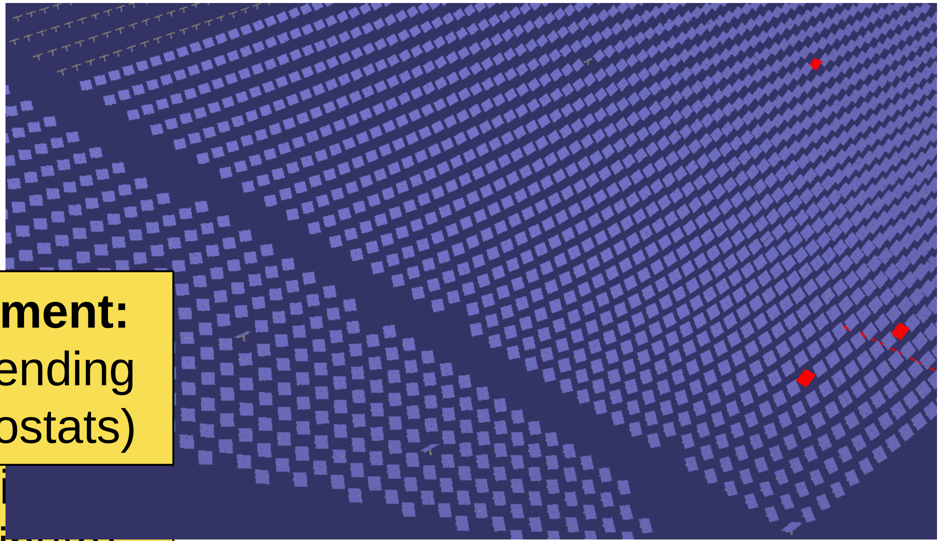
Asynchronous definition





Synchronous adjustment

- List of heliostats to be modified
- Modification
  - Live defocus
  - Live change of tracking error
  - New aimpoint
- Time auto adjustment
  - DNI
  - Sun position change

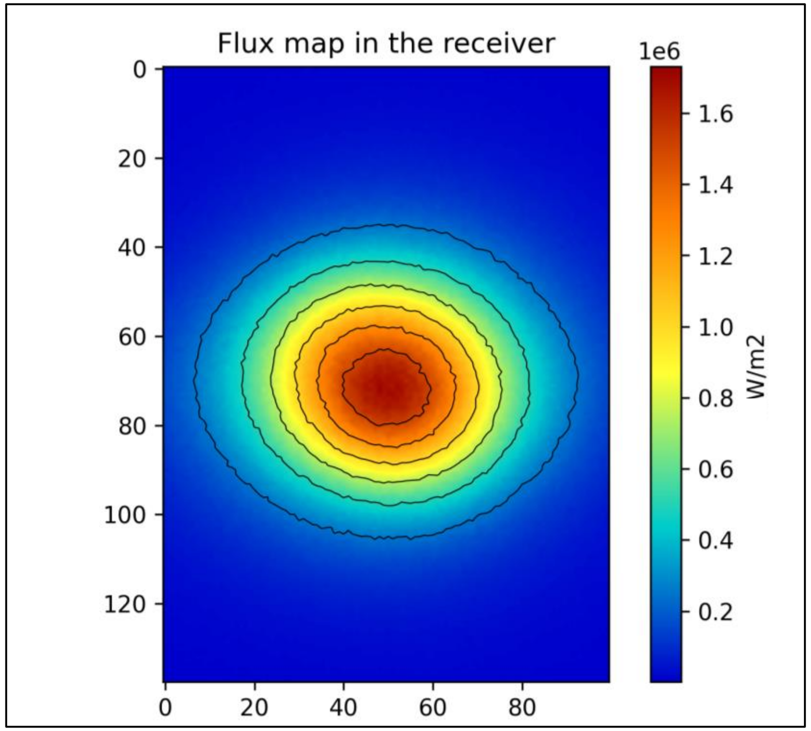


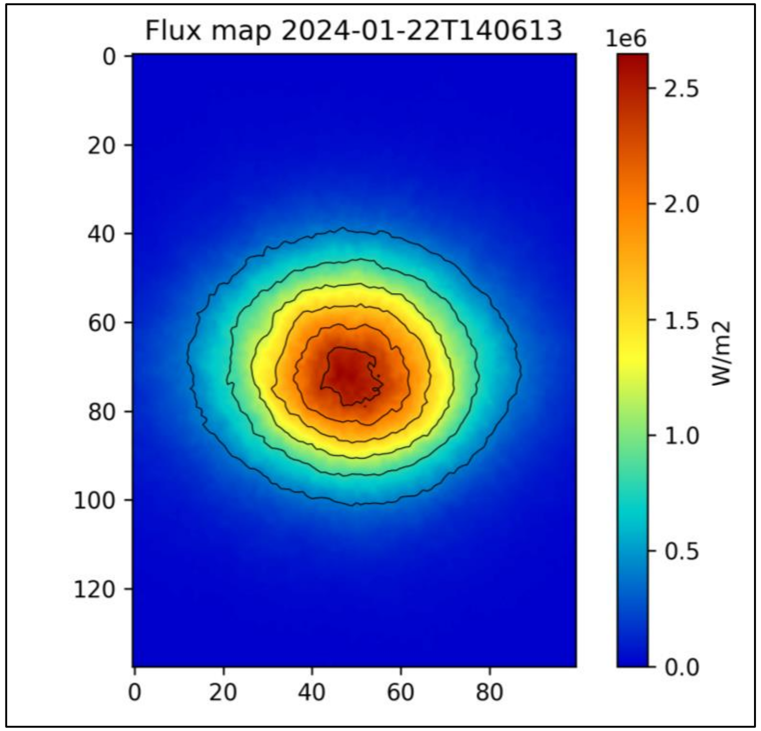
Real time adjustment:
latency < 7s (depending on amount of heliostats)

defined automati
(less than one minute)

RESULTS: PROOF OF CONCEPT

Real time variation in the result





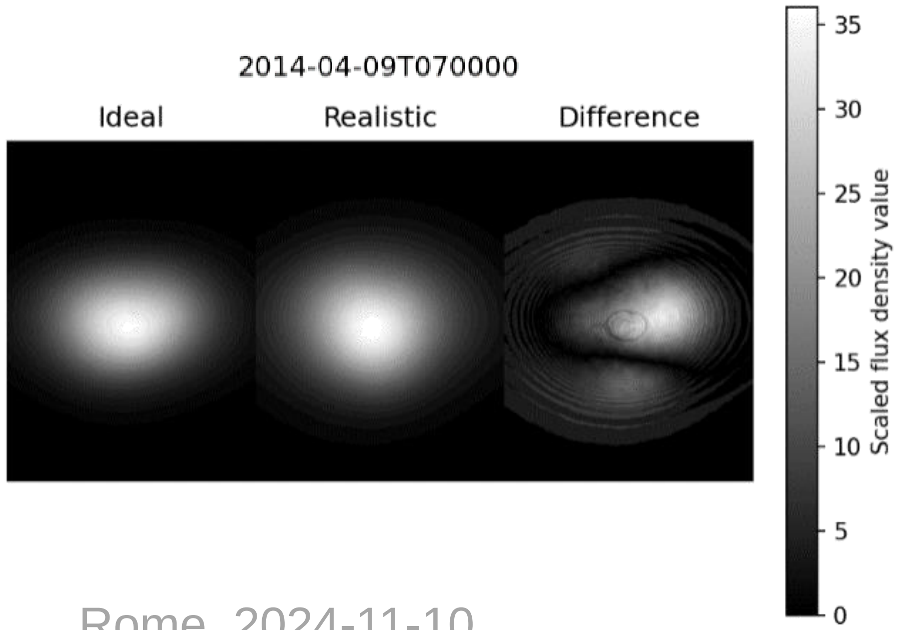
Results labelled and saved in local disk automatically (process latency ~2s)

RESULTS: TRACKING ERROR MODELS

- **Application of the digital twin for checking the influence of tracking error models**
  - Grayscale images used for this case
  - Images normalized against peak conditions of the period → Needed for bright level assessment
  - 931 meteorological situations logged in experiments between 2014-16 (TestRec)

Max DNI		Conditions			
944.1		47.7	189.3	4/12/2016	2:00:00 PM

- **Cherry-picked case** (09.04.2014 @ 7:00:00 AM)



Influence of modelling tracking error → 6%* of RMSE and /m² (20-25%)

16 combinations of heliostats tested → Dataset of 15827 pairs of images

* RMSE is even underestimated because most of the pixels are black due to the dimension of the spot

Results: AI-enhancement

CURRENT STATUS: U-NET CORRECTION

- **Pre-training analysis performed (sim2sim)**
- Best hyperparameters found:
  - Learning rate: 0.001, ReduceLROnPlateau → Factor: 0.03
  - Epochs: 50
  - Batch size: 16

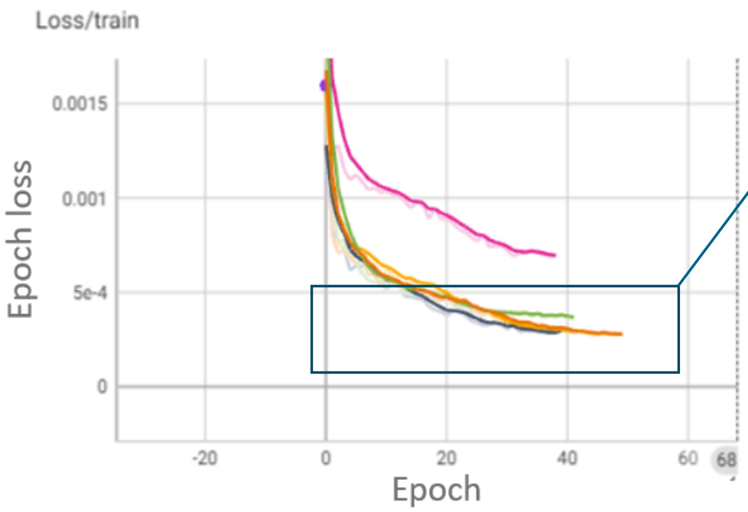
- Employed loss function: MSE pixel-wise
- Employed accuracy function:
  - Based on the total amount of power collected by evaluation plane comparing output and label
  - Examines differences between flux measured in the output of the model $(X_{r,i})$ and the target $(\hat{X}_{r,i})$ pixel-wise and adds the values

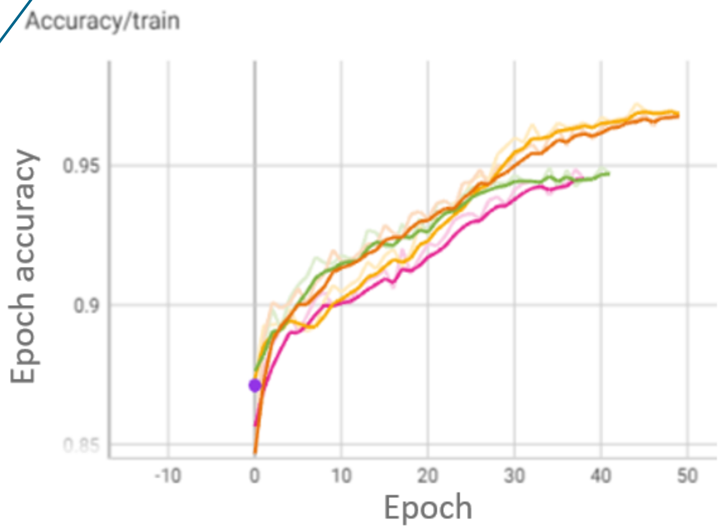
$$A_{pix,X} = \frac{\sum_i \left| X_{r,i} - \hat{X}_{r,i} \right|}{\sum_i \left| \hat{X}_{r,i} \right|}$$

CURRENT STATUS: RESULTS

- **Loss and accuracy plots**

Successful augmentation: same generalization as in original dataset





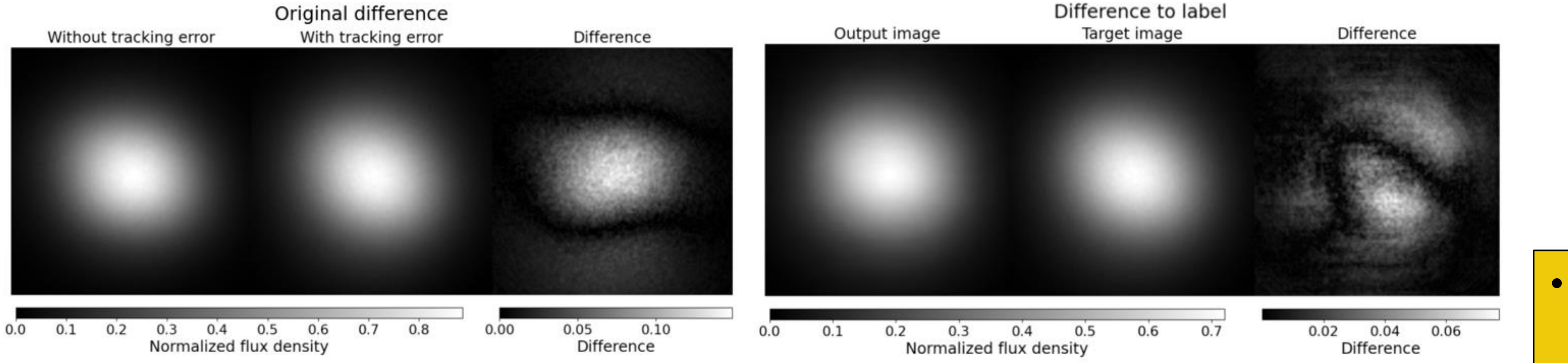
- MSE (loss) reduced from 6% to 0.03%
- Accuracy reaching 97.5%

- Different curves represent different augmentation techniques:
  - Dark blue: original dataset
  - Pink: random noise maps (amplitude of 7%), horizontal and vertical flips each applied to 40%
  - Green: random noise maps (amplitude of 3%), horizontal and vertical flips each applied to 25%
  - random noise maps (amplitude of 1.25%), horizontal and vertical flips each applied to 25%
  - Dark orange: random noise maps (amplitude of 3%), horizontal and vertical flips each applied to 25%

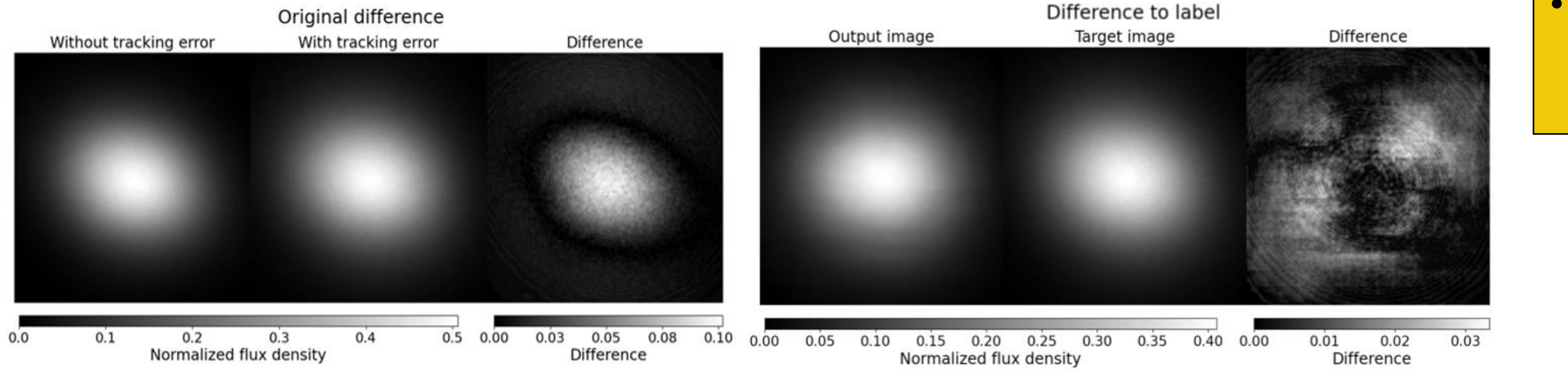
CURRENT STATUS: RESULTS

- **Inference results**

2019-05-07 @ 13:43:59 → High intensity



2018-06-04 @ 12:14:52 → Medium intensity

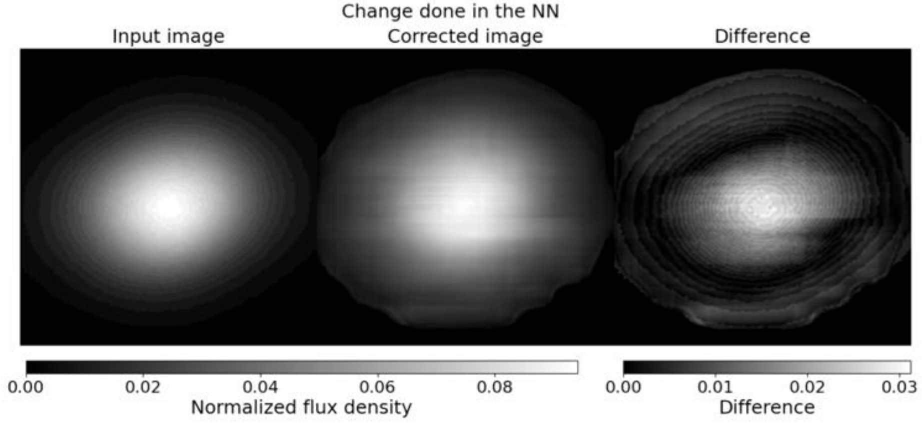


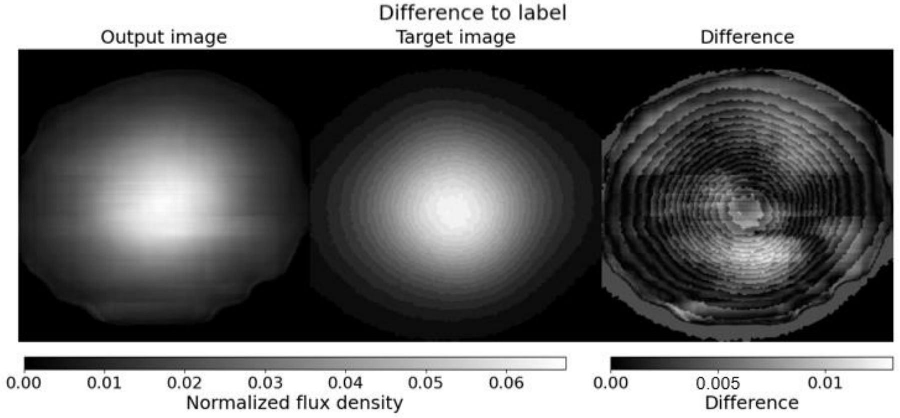
- Peak differences: from 25% to <10%
- Better distribution: avoid hotspot effect
- Able to predict tracking error effects with accuracy

CURRENT STATUS: RESULTS

- **Inference results**

2018-06-14 @ 07:43:59 → Very low intensity

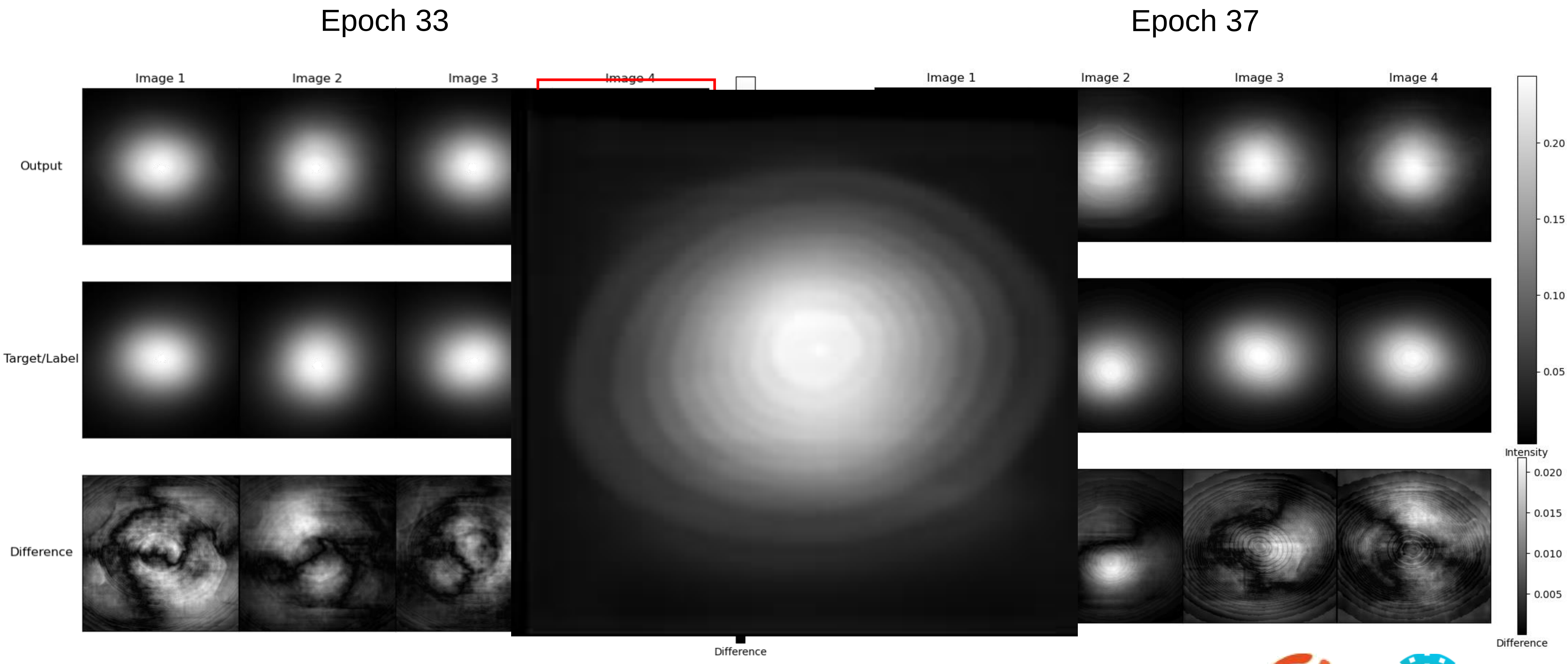




Also valid for low intensities

CURRENT STATUS: UNET + AG

- **Attention gates →** Better feature recognition: improvement of isolines

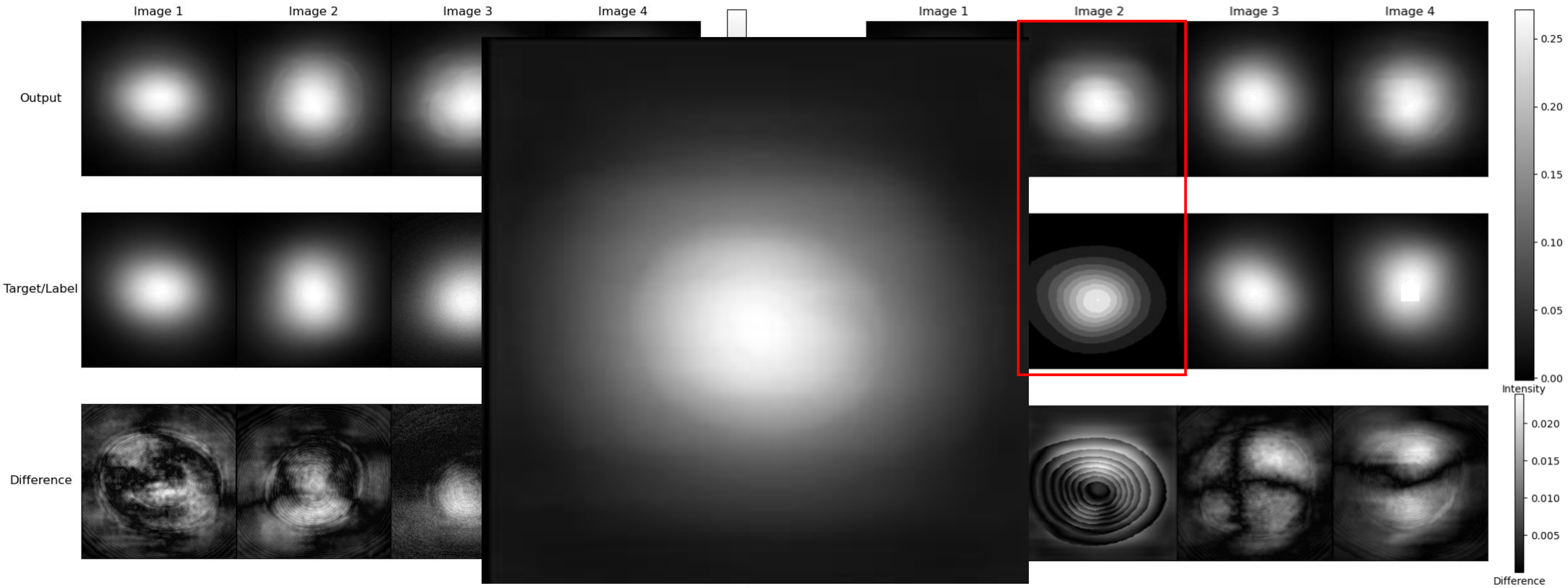


CURRENT STATUS: UNET3+

- **Deep and dense connection**

Epoch 36

Epoch 45



CURRENT STATUS: SUMMARY

	UNet	UNet + AG	UNet3+
Training time (h)	~8	~10	~20
Accuracy (%)	97.5	98.7	98.5
Loss (%)	0.034	0.022	0.024
Trainable in commercial laptop? (Y/N)	Y	N	N
Topography attention (Y/N)	N	Y	N
Noise handling? (Y/N)	N	Y	Y
Tracking errors predicted? (Y/N)	Y	Y	Y

THE END

Thanks for listening!

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Marie Skłodowska-Curie Actions